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(54) **METHOD AND APPARATUS FOR THE CLASSIFICATION OF AN ARTICLE**

VERFAHREN UND VORRICHTUNG ZUR ARTIKELKLASSIFIZIERUNG

PROCEDE ET APPAREIL DE TRI D'UN ARTICLE

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Description

The invention relates to a method and apparatus for the classification of an article, particularly, but not exclusively, a monetary unit such as a banknote or a coin.

Such methods are advantageously used in vending machines, change machines and the like, where classification is carried out, on the one hand, according to value, for example between one-, two- and five-dollar notes, and/or, on the other hand, between originals and copies or counterfeits thereof.

The method of the invention can also be applied quite generally for the classification of test specimens, for example of images, graphs, documents, stamps or signals.

It is known to process intensity values of electromagnetic radiation reflected by image parts of a test specimen in such a manner that the test specimen can be compared with a pixel matrix (EP 0 067 898 B1) of an original, or that differences from an original are expressed and evaluated in the form of an angle between two n-dimensional vectors (DE 30 40 963 A1) or as a cross-correlation function (EP 0 084 137 A2).

EP-A-0 472 192 describes a banknote validator in which a measuring system derives optical measurements of individual areas of a banknote, these measurements being amplified and A/D converted before being stored in a memory. The data is divided into blocks, and the data within each block is averaged. The validator stores sets of standard average value data, each set representing a standard banknote in a particular orientation. The standard average data is compared with the averages derived from the measurements, so that for each set of data there is produced a total value which represents the sum of the absolute differences between the standard average data and the averaged measurements in the respective blocks. The set associated with the smallest total value represents the denomination of the banknote.

EP-A-0 165 734 also discloses a banknote tester in which optical measurements are made to derive pixel values associated with respective areas of the banknote. Each pixel value is compared with a respective value which is derived from a corresponding pixel in a master image together with other pixels in the neighbourhood of that corresponding pixel.

It is further known that valid value ranges of at least two measurements of a coin or a banknote describe a rectangle (GB 2 238 152 A) or an ellipse (GB 2 254 949 A) and that the coin or the banknote is accepted if a point formed by at least two measurements lies inside the rectangle or the ellipse.

It is also known (CH 640 433 A5) to compare various measurable physical variables of a test specimen with corresponding stored threshold values substantially independently of one another and, after successful classification, to correct the threshold values using the measurable variables of the accepted test specimen.

Various formulations for learning classifiers are furthermore known (H. Niemann: "Klassifikation von Mustern" - Berlin, Heidelberg, Berlin, Tokyo: Springer 1983) in which the class ranges are continuously altered using classified patterns and which require a considerable amount of calculation during the classification, which, in practical use, may lead to unacceptable response times.

In a classification process, particularly for classification of a monetary unit, differentiation between originals and copies/counterfeits thereof is especially problematical since, on the one hand, originals and copies/counterfeits thereof are extremely similar to each other or differ only slightly in their features and, on the other hand, only a small number of different copies/counterfeits of an original is available. Indeed, some counterfeits may not be available at all when the process is set up. A further problem is that the features of an original, for example the features of all genuine ten-frank notes of different issues, may show a wide dispersion.

It would be desirable to provide a process for the classification of a pattern, with which a pattern can be reliably classified even when features of one class differ little from the corresponding features of at least one other class and/or when features of the class are widely dispersed, and to create a device with which the process can be carried out. It would also be desirable to provide a process which is likely to be capable of distinguishing between genuine and counterfeit articles of currency, even when the counterfeits are not available when the process is being set up.

Aspects of the present invention are set out in the accompanying claims.

An illustrative embodiment of the invention is described in detail below with reference to the drawings, in which:

Fig. 1 is a block diagram of a device for classifying a pattern;
Fig. 2 shows the principle of a classification system;
Fig. 3 shows a recognition unit of the classification system;
Fig. 4 indicates one way in which the recognition unit may operate; and
Fig. 5 is a diagram of the activity spaces of a recognition unit of the classification system.

In Fig. 1, reference numeral 1 denotes a measuring system substantially comprising an inlet 2 and a transport system, not shown, for a test specimen 3 and a group of sensors 4 with which a pattern of the test specimen 3 is measured. The measuring system 1 is connected by a feature channel 5 to a preliminary processing system 7 having at least one preliminary processing activity 6. A classification system 8 is connected via an input channel 9 to the preliminary processing system 7 and via a first output channel lOa to a service system 11. If necessary, the classification system 8 is also connected to the measuring system 1 via a second output

channel lOb. The measuring system 1, the preliminary processing system 7, the classification system 8 and the service system 11 are, therefore, connected by channels substantially to form a chain which is terminated by the service system 11.

If necessary, an initialisation system 12 is connected to the classification system 8 via an initialisation channel 13.

Fig. 2 shows by means of a data flow diagram the construction in principle of the classification system 8 arranged between the preliminary processing system 7 and the service system 11. In the method of representation chosen, which is known from the literature (D.J. Hatley, I.A. Pirbhai: Strategies for Real-Time System Specification, Dorset House, NY 1988), a circle denotes an activity, a rectangle a terminator and an arrow a communication channel for the transmission of data and/or results, the tip of the arrow pointing substantially in the direction of flow of the data. Furthermore, an arrangement consisting of two activities connected by a communication channel is equivalent to a single activity that fulfils all the functions of the two activities.

Activities are implemented in the form of an electronic circuit and/or in the form of a process, a part of a program or a routine.

The classification system has an output unit 14 which is connected to the two output channels 10a and 10b, and a specific number n of recognition units are connected to the output unit 14, there being shown in Fig. 2, for the sake of a general and simple representation, only three of the n recognition units actually present.

15.1 denotes a first recognition unit, which is connected via a first input data channel 16.1 for a first input vector AGF_1 to the preliminary processing system 7 and via a first output data channel 17.1 for a first signal K_1. 15.2 further denotes a second recognition unit, which is connected via a second input data channel 16.2 for a second input vector AGF_2 to the preliminary processing system 7 and via a second output data channel 17.2 for a second signal K_2. Finally, 15.n denotes an nth recognition unit, which is connected via an n-th input data channel 16.n for an n-th input vector AGF_n to the preliminary processing system 7 and via an n-th output data channel 17.n for an n-th signal K_n.

Three dots 18 indicate the other recognition units, not shown, each of which is connected via a further input data channel to the preliminary processing system 7 and via a further output data channel to the output unit 14, each further input data channel being able to transmit a further input vector AGF and each output data channel being able to transmit a further signal K.

The input channel 9 (Fig. 1) is represented in Fig. 2 by the n input data channels 16.1 to 16.n.

Each of the recognition units 15.1 to 15.n is arranged to determine whether its input vector AGF represents a particular, respective target class, and to provide an output signal K in response thereto. Advantageously, there are defined for an original of one class as many target classes (and corresponding recognition units 15) as there are scanning directions available in the measurement of physical features of the original in the measuring system 1. If the test specimen is a document printed on both sides, then, for example, the four scanning orientations "face-up moving forwards", "face-up moving backwards", "face-down moving forwards" and "face down moving backwards" could be available.

In the classification of a test specimen that is either a ten-frank note, a twenty-frank note or a fifty-frank note with each of the four possible scanning directions, twelve different target classes, for example, are obtained.

The output unit 14 informs the service system 11 and/or the measuring system 1 either of the target class of the test specimen 1 ascertained by the classification system 8 or of the fact that the test specimen 1 is a counterfeit. Advantageously, the output unit indicates the target class of the test specimen 1 when, and only when, exactly one of the n recognition units 15.1 to 15.n recognises its target class. Otherwise the test specimen is indicated to be a counterfeit.

In the classification of the test specimen 1, the n recognition units 15.1 to 15.n may operate successively (for example using a single processor executing sequential processing), but advantageously they operate concurrently, or at least partly concurrently.

Our Swiss Patent Application No. 00 753/92-4, and corresponding U.S. Application Serial No. 08/013,708, filed 4th February 1993, and EP-A-560023 disclose a measuring system and a processing system for generating a feature vector from values of measured features of a test specimen. The arrangements disclosed therein for this purpose may also be used to advantage in apparatus according to the present invention. In particular, referring to the description relating to Figures 1 and 2 in the above-mentioned cases, the receiving system 1, the pre-processing system 7 and the activities 14 and 17 in the classification system 8, which are performed on the basis of the data received from the pre-processing system and the data stored in the data memory 23, may also be used in an arrangement according to the present invention, although the activities 14 and 18 would in the present case be performed by the preliminary processing system 7 shown in the accompanying Figure 1.

In one specific example, the measuring system 1 may be arranged to scan a banknote along N lines, using optical sensors. There may be for example three lines, two on one face of the banknote and one on the reverse face. Each scan line will contain L individual areas, which are scanned in succession. In each area, there may be for example measurements of M different features (for example the reflectance intensities of red, green and infra-red radiation, where M = 3). The total number of measurements for the banknote would therefore be equal to N x M x L. These measurements are delivered to the preliminary processing system 7 along

the feature channel 5. The system 7 will then derive, for each scanning point, a k-dimensional local feature vector. The individual components of the vector may represent the parameters described in the earlier applications, or alternatively may represent:

(a) The spectrally normalised intensity of the infra-red radiation (i.e. the reflection intensity of the infra-red radiation divided by the sum of the reflected intensities of the infra-red, green and red radiation).
(b) The spectrally normalised intensity of the red radiation.
(c) The spatially normalised intensity of the infra-red radiation (i.e. the intensity of the reflected infra-red radiation divided by the sum of the intensities of the infra-red radiation for all scanned areas of the current track).
(d) The spatially normalised intensity of the red radiation.
(e) The spatially normalised intensity of the green radiation.

Instead of using these values directly, they can if desired be transformed using stored data representing mean values and dispersion factors for those components. For example, each of the k components may comprise the difference between the spectrally (or spatially) normalised intensity value and the average of that value, divided by the dispersion factor.

This will result in the calculation of a k-dimensional local feature vector $LFV_{i,1}$ (where i = 1 to N, and l = 1 to L) for each scanned area, this vector varying for each target class (because the stored average values and dispersion factors differ depending upon target class).

If desired, each component of each of the k-dimensional vectors can then be compared with a stored range (which may differ for each target class), and the test specimen may be classified as a counterfeit if one (or a predetermined number) of the components lies outside the respective range. Thus, it is possible to avoid further processing operations if the first pre-processing operation indicates that the test specimen produces measurements significantly outside those expected for genuine items.

A second part of the pre-processing operation involves combining the local feature vectors $LVF_{i,1}$ for each of the lines into a single k-dimensional global feature vector GFV_i. There would thus be produced N such global feature vectors for each test specimen. The global feature vectors may be formed by summing the individual components of each of the local feature vectors associated with the line. In addition, if desired, a further transformation operation can be performed, similar to that carried out in the first stage of the pre-processing operation. Thus, each summed component may be adjusted by subtracting from it a stored average value for this component, and dividing by a dispersion factor. Again, these values may vary depending upon the target class.

The global feature vectors may also be compared with stored ranges. In this case also, this may be achieved by comparing each component of the k-dimensional global feature vector with a respective range. The test specimen is deemed counterfeit if one, or a predetermined number, of vector components lies outside the respective range.

The third stage of the pre-processing operation involves combining the N global feature vectors GFV_i. This is achieved by separately summing the respective components of the vectors to form a single global surface feature vector AGF, having k dimensions. Again, each component may be transformed in a similar manner to the transformations mentioned above to take into account stored average and/or dispersion data.

The pre-processing system 7 thus results in a surface feature vector AGF which will differ depending upon the target class, assuming that transformation operations taking into account stored data appropriate to the target classes are used. Respective surface feature vectors AGF_1 to AGF_n are then presented to the respective recognition units 15.1 to 15.n, as shown in Figure 2.

It is to be noted that any one or all of the transformation operations mentioned above could be omitted. In principle, it would be possible to present the same feature vector AGF to all of the recognition units 15.1 to 15.n, and just use the individual characteristics of the recognition units for discriminating between classes. However, the use of one or more of the transformation operations has the advantage of normalising and compressing the data. Furthermore, it would be possible to arrange for stored data of a target class to be updated whenever the output unit 14 indicates that the test specimen corresponds to the target class. The use of a transformation operation based on this updated data would therefore avoid or mitigate problems due to drift, e.g. in the measuring components.

The dimension k can in principle be freely selected and therefore can advantageously be adapted to the test specimen 3 and/or the measuring system 1 and/or the preliminary processing system 7 and/or the classification system 8. The dimension k is, in the above example, 5, but may be smaller or greater.

Advantageously, each of the n recognition units 15.1 to 15.n is in the form of one neural network. A preferred arrangement of the recognition unit 15.1 (Fig. 2) to 15.n, which is shown in Fig. 3, comprises an input layer 19, a neuron layer 20 and an output layer 21.

The input layer 19 has a fixed number k of inputs and the neuron layer 20 has a pre-determined number m of neurons. The output layer 21 advantageously has an output component 22 having one output 23 and m inputs.

In Fig. 3, for the sake of a general and simple representation, only three of the k inputs actually present and only three of the m neurons actually present are shown.

20.1 denotes a first neuron, 20.2 a second neuron and 20.m an m-th neuron, whilst a first input of the input layer 19 is designated 19.1, a second input 19.2 and a k-th input 19.k.

Advantageously, each of the m neurons has k inputs, each input of each neuron 20.1 to 20.m being connected by a respective input weighting component 24_{ji} to each of the k inputs 19.1 to 19.k of the input layer 19; in the reference numeral for the input weighting component 24_{ji}, the index i refers to the i-th input 19.i of the input layer 19 and the index j refers to the j-th neuron 20.j connected to the input 19.i by the input weighting component 24_{ji}. To give an example of this, the second neuron 20.2 is connected at its input side by the input weighting component 24_{2l} to the first input 19.1 of the input layer 19 and further connected by the input weighting component 24_{2k} to the k-th input 19.k of the input layer 19.

Each neuron 20.j of the m neurons 20.1 to 20.m is connected at its output side via a respective output weighting component 25.j to the output component 22, the index j in the reference numeral for the output weighting component referring to the j-th neuron 20.j.

The first three dots 26 indicate the inputs 19.x, not shown in Fig. 3, of the input layer 19, the index x being, in the complete integer range, greater than two and less than k, whilst the second three dots 27 represent the neurons 20.y that are not shown, the index y being, in the complete integer range, greater than two and less than m.

A target class lies inside the k-dimensional space, it being possible to describe a single target class in general by a plurality of vectors that are different from one another. The part of the k-dimensional space that can be occupied by a target class is advantageously divided into sections in a preparatory or learning phase of the process, the sections adjoining or being separate from one another in the space, and each section being determined by a respective target vector W which advantageously is k-dimensional.

The target class, therefore, is described in general by a number m of different prototype or target vectors W_j, it being possible for the number of target vectors W_j of different target classes to be different. In the embodiment of Fig. 3, each of the m neurons 20 is associated with a respective target vector W_j of the target class. A target vector W_j of a target class is defined by the weighting components 24_{ji} connected to the neuron 20, which are advantageously determined by learning, and, if necessary, continuously adapted, in the preparatory phase. The number m may for example be from 5 to 10.

In operation of each of the recognition units 15.1 to 15.n, it is assumed that X represents the associated one of the input surface features vector AGF_1 to AGF_n. In each unit there is determined a target vector W_c that, amongst all the m target vectors W_j of the target class, has the least value of a distance d from the surface feature vector X. The distance d is advantageously the Euclidean distance between the target vector W_j and the surface feature vector X. However, the distance d may be a different variable which can determine that target vector W_c which, of the m target vectors W_j, is closest to the feature vector X. Another example of an advantageous variable for the distance d is the absolute distance or the Manhattan (city block) distance between a target vector W_j and the feature vector X.

The Euclidean distance d between two k-dimensional vectors W_j and X is defined as follows:

$$d_j = [(W_1-X_1)^2 + (W_2-X_2)^2 + \ldots + (W_k-X_k)^2]^{1/2}$$

(G1).

The process for the classification of the pattern that can be described by a k-dimensional feature vector X can especially advantageously be carried out concurrently if the classification system 8 has at least one neural network. Advantageously, the neural network is a so-called LVQ (Learning Vector Quantisation) type according to Kohonen (Teuvo Kohonen et al.: Statistical Pattern Recognition with Neural Networks, Proceedings of 2th Annual IEEE International Conference on Neural Networks, volume 1, 1988, pages 61..68) which has the structure shown in Fig. 3.

With j from 1 .. m, the values of the input weighting components $24_{.j1}$ .. $24_{.jm}$ of the neuron 20.j are advantageously designed according to a target vector W_j, and are variable. The values of the input weighting components $24_{.j1}$ .. $24_{.jm}$ are advantageously determined and, if necessary, adapted in the learning phase. Each neuron 20.j determines at least the distance d_j by receiving at each input the difference between the input weighting component 24_{ji} and a component of the input vector X, by summing the squares of these differences, and then taking the square root. The neuron 20.j - for j from 1 .. k - transmits to the output layer the logic value "1" only when it has the minimum distance d_c.

Advantageously, the output component 22 is an OR-gate and the values of the weighting components 25.1 to 25.m are set to one. If one recognition unit outputs a logic "1", the output component 22 transmits this as an indication of a recognised test specimen, and preferably also transmits an indication of which recognition unit issued the logic "1", thereby indicating the target class.

A normal LVQ network would be arranged so that the neuron 2O.c with the minimum distance would always transmit the logic value "1". In the present embodiment, the neuron 20.c with the minimum distance d_c additionally tests for two further conditions (G2) and (G3), set out below. A logic "1" is transmitted only if all three conditions (G1), (G2) and (G3) are fulfilled; otherwise, the neuron 20.b transmits the value logic "0".

Accordingly, the determined target vector W_c and the feature vector X are precisely analysed in further

process steps in such a manner that it is certain, with an expected reliability, whether the feature vector X is to be assigned to the target class.

In a first advantageous process step, the greatest magnitude component of the surface feature vector X is compared with a limiting parameter q_{max}, the parameter q_{max} advantageously being determined in the learning phase. Using a function maximum(), the following condition is therefore obtained:

$$\text{Maximum}(|X_1|, |X_2|, \ldots, |X_k|) \leq q_{max} \qquad (G2).$$

In a second advantageous process step, the subtraction W_c-X is carried out component by component for all k components and the amount of the difference of two corresponding components is compared with a space limiting parameter $q_{c1max} .. q_{ckmax}$ assigned component by component, the k parameters $q_{c1max} .. q_{ckmax}$ advantageously being determined in the learning phase. With i from 1 to k, the following condition is therefore obtained:

$$|W_{ci} - X_i| \leq q_i \qquad \text{with i from 1 .. k} \qquad (G3).$$

The feature vector X is assigned to the target class of the target vector W_c when, and only when, the conditions (G2) and (G3) apply.

Fig. 4 shows by way of example how one neuron 20.j may operate. A first part 20'.j receives inputs I_1 from the weighting components 24_{ji}, calculates the distance d_j and sends this to a controlling unit 30. This compares the distances received from all the neurons, and, for the neuron with the shortest distance, sends a signal to a second part 20".j of the neuron. This has inputs I_2, I_3 receiving values q_{max}, q_i permitting the part to test for conditions (G2), (G3). If the conditions are met, a logic "1" is output on output line O.

Each target vector W_j - for j from 1 .. k - of a target class advantageously lies in a part R_j of the k-dimensional space that is bounded by polygons of a Voronoi diagram (J.M. Chassery et al.: "Diagramme de Voronoi applique à la segmentation d'images et à la detection d'événements en imagenrie multi-sources, Traitement du Signal, volume 8, No. 3).

An activity space of the neuron 20.j - for j from 1 .. k - is advantageously a limited region of the part R_j of the space, the limitation being achieved by conditions (G2) and (G3).

Figure 5 is a representation of the activity space for a particular recognition unit. For the purpose of simplification and clarity, it is assumed that the input vector X has two dimensions (i.e. k = 2), lying in the plane of the diagram, and that there are four neurons 20.j. Each neuron is associated with a target vector W_c, the target vectors being indicated on the diagram by reference numbers 1, 2, 3 and 4. The lines V_1 to V_6 represent the boundaries of the Voronoi polygons. Thus, the line V_1 between vectors 1 and 2 is defined by those vectors which are equidistant from the vectors 1 and 2.

The boundaries B1, B2, B3 and B4 are created by condition (G2), and exclude any vectors which lie substantially outside the area of interest. It is noted that condition (G2) could alternatively be tested as a final part of the pre-processing stage, so that a vector X is only presented to the classification stage if condition (G2) is met.

Within each Voronoi polygon area, there is a shaded area defined by rectilinear boundaries which are created by condition (G3). Without condition G3, any vector lying in the polygon containing vector 2 would activate the associated neuron. However, because of condition (G3), only vectors lying within the shaded area containing vector 2 will activate the neuron, so that the activation area for that neuron has been restricted. By applying different restrictions to the different neurons, it will be seen from Figure 5 that the overall shape of the activation area for the complete recognition unit can be complex, and can be controlled to achieve good acceptance of genuine test specimens and good rejection of counterfeits.

It will be seen from Figure 5 that the range limits for one component of the vector (e.g. 2 x q_{31}, being the limits for the first component of vectors lying within the activity space of neuron 3) may be of a different magnitude from the ranges for other components (e.g. 2 x q_{42}, being the range limit for the second component of vectors lying in the activity space of neuron 4). Generally, there would also be stored different range limits for different neurons, so that the range limit $2q_{42}$ for the second component of vectors lying in the activity space of neuron 4 would not necessarily be the same as the range limit $2q_{22}$, being the range limit for the second component of vectors lying within the activity space for neuron 2. Furthermore it is not essential that the boundaries be symmetrically located about the target vectors 1, 2, 3 and 4.

As shown in Figure 5, condition (G3) applies rectilinear limits to the activity spaces. This results from the fact that each component of the difference between the input vector X and the target vector W_c is compared separately with a respective limit value. This allows for simple processing. However, it would alternatively be possible to have other conditions apply, such as a distance measurement. For example, the distance measurement d_c which is derived when determining the neuron 20.c associated with the shortest distance between the target vector W_c and the input vector X may be compared with a range to limit the activity space for the neuron. The result of this would be that the shaded areas in Figure 5 would no longer have rectilinear boundaries, but would instead have elliptical boundaries, possibly intersected by the lines V_1 to V_6.

It will also be appreciated that the boundaries B1 to B4 also need not be symmetrically distributed, and there

may be different values of q_{max} for different components of the input vector X.

Because the recognition units 15.1 to 15.n are, in known manner, learning neural networks, the values of their m times k input weighting components 24_{ji} - with j from 1 to m and i from 1 to k - can best be determined by teaching in known manner. For example, during the training process the apparatus can be fed with test specimens of known target classes, and known counterfeits. Within each recognition unit, it is determined which target vector is closest to the surface feature vector X. If the recognition unit is associated with the correct target class of the test specimen, then the weighting components associated with that target vector are adjusted so as to bring it closer to the feature vector X. If the test specimen is not of the associated target class, the weighting components are adjusted to move the target vector away from the feature vector (X). The weighting components associated with the other target vectors of that recognition unit are not adjusted. (In an alternative arrangement, the other weighting components may also be adjusted using an adaptive mechanism to increase the convergence speed.) The amounts by which the weighting components are adjusted can initially be large, but can be decreased as the training procedure progresses. This allows a very rapid iterative training process which derives the target vectors and hence the discriminant surfaces defined by the boundaries of the Voronoi polygons.

As a result of the training process, it is possible to arrange for the target vectors for a particular target class to be relatively close together, and to be distant from vectors X which are produced as a result of testing counterfeit specimens. Nevertheless, there may be other counterfeits, perhaps not used in the training process, which would produce vectors within the Voronoi polygon associated with a target vector, such as shown at P in Figure 4. However, by applying conditions (G2) and (G3), limits are placed on the permissible values for the input vector X so it is possible to avoid erroneously accepting such a vector P as a genuine specimen. By using a neural network-type arrangement to perform the classification according to discriminant data derived in an iterative training process, but then applying one or more boundary tests to limit the acceptance volume, it becomes much easier to avoid erroneously accepting counterfeits, even when those counterfeits are not used in the training process.

The limiting parameters q_j and q_{jimax} - with j from 1 to m and i from 1 to k - can advantageously also be determined for all target classes by teaching in known manner. Alternatively, they may be separately determined in such a manner as to reduce the activity space sufficiently to minimise the risk of counterfeits being classified as genuine specimens.

One possibility would' be for the learning procedure to record which neuron 20.c is associated with the shortest distance whenever a test specimen is recognised during the training session. The ranges q_i for each of the k components of the vector W_c can then be calculated to be the standard deviation (or proportional to the standard deviation) of the respective component of the vectors X generated in response to those test specimens. Any calculated range can then be adjusted, if necessary, to exclude any vectors X generated in response to other test specimens.

If necessary, the starting values required for teaching are entered by means of suitable test specimens 1, or they are transmitted to the classification system 8 by the initialisation system 12.

As indicated above, the parameters used in the transformations applied to the feature vectors may be updated each time a specimen has been tested and found to correspond with a target class. Alternatively, or additionally, the weighting components may be updated also, so that the neural networks 15.1 to 15.n are continuously being re-trained during operation of the apparatus. The limiting parameters used in condition (G2) and/or (G3) may also be updated in a similar manner.

Although the above embodiment has been described in the context of measurements of reflected colours, the invention is equally applicable to other types of measurements, for example detection of lines of magnetic ink on a banknote, or detection of surface contours on a coin.

The above embodiment stores data (the weighting components 24_{ji}) defining the target vectors. Alternatively, it is possible only to store data defining the discriminant surfaces, i.e. the boundaries of the Voronoï polygons.

Claims

1. A method of validating an article of currency by determining whether the article belongs to a target class associated with a particular denomination in a particular orientation, the method comprising producing a k-dimensional feature vector (X) describing the article, determining from among a plurality of target vectors all associated with said target class that target vector (W_c) which is closest to the feature vector (X), and designating the article as belonging to the target class if the components of the feature vector (X) meet a predetermined criterion indicating that the feature vector (X) lies within a predetermined boundary containing the closest target vector (W_c).

2. A method as claimed in claim 1, wherein the components of the feature vector (X) are determined to meet said predetermined criterion if the closest target vector (W_c) has a predetermined relationship with the feature vector (X).

3. A method as claimed in claim 2, wherein the prede-

termined relationship is different depending on which target vector is closest.

4. A method as claimed in any preceding claim, wherein the components of the feature vector (X) are determined to meet said predetermined criterion if the individual components each meet a respective criterion.

5. A method as claimed in claim 4, wherein the components of the feature vector (X) are determined to meet said predetermined criterion if the difference between each individual component of the target vector (W_c) and the corresponding component of the feature vector (X) is within a predetermined range.

6. A method as claimed in any preceding claim, wherein each of the target vectors associated with a target class lies within a respective Voronoï polygon, and wherein said predetermined criterion restricts the area of the Voronoi polygon within which a feature vector (X) is deemed to represent an article of the target class.

7. A method as claimed in any preceding claim, wherein the target vector (W_c) closest to the feature vector (X) is determined by measuring the Euclidean distance between the target vector (W_c) and the feature vector (X).

8. A method as claimed in any preceding claim, wherein at least one neural network is used to determine the target vector (W_c) closest to the feature vector (X).

9. A method as claimed in claim 8, wherein the neural network is an LVQ network.

10. A method as claimed in claim 8 or claim 9, wherein, for every target vector of a target class, the distance d to the feature vector (X) is calculated using one neuron or neuron-like part.

11. A method as claimed in any preceding claim, including the step of deriving the feature vector (X) using stored statistical data representative of the target class.

12. A method as claimed in claim 11, including the step of updating the statistical data representative of the target class on the basis of measurements of a test specimen determined to belong to that target class.

13. Apparatus for validating an article of currency, the apparatus comprising a measuring system, a preliminary processing system and a classification system for the classification of an article that can be described by k-dimensional feature vector (X), the preliminary processing system being responsive to measurements of physical features of a test specimen supplied by the measuring system for deriving the k-dimensional feature vector (X) and supplying the feature vector to the classification system, the classification system comprising a recognition unit for determining whether or not the article belongs to a target class representing a particular denomination in a particular orientation, the recognition unit being operable to determine which, amongst a plurality of target vectors associated with that target class, is the closest target vector (W_c) to the feature vector (X), and to designate the article as belonging to the target class if the components of the feature vector (X) meet a predetermined criterion indicating that the feature vector (X) lies within a predetermined boundary containing the closest target vector (W_c).

14. Apparatus according to claim 13, wherein the recognition unit comprises an input layer, and a neuron layer connected at its input side to the input layer via input weighting components and at its output side to an output layer, the input weighting components defining the target vectors for the recognition unit.

15. Apparatus as claimed in claim 14, wherein the weighting components each have values which have been determined during a training process.

16. Apparatus as claimed in claim 14 or 15, including means for varying the values of weighting components in accordance with measured physical features of a test specimen when that test specimen has been found to belong to the target class of the recognition unit including those weighting components, and when the weighting components define the target vector closest to the feature vector (X) for that specimen.

17. Apparatus as claimed in any one of claims 13 to 16, wherein the preliminary processing system is operable to derive different feature vectors (X) for respective target classes on the basis of different sets of statistical data each associated with a respective denomination, the respective feature vectors (X) each being applied to a respective recognition unit.

18. Apparatus as claimed in claim 17, including means for modifying the statistical data related to a denomination in accordance with measured physical features of an article which has been tested in response to determining that the article belongs to the class associated with that denomination.

19. A method of validating an article of currency, the

method comprising providing a signal indicating that the article of currency belongs to a target class associated with a particular denomination in a particular orientation, if (a) a feature vector (X) descriptive of the article has been determined to lie within one of a plurality of Voronoï polygons associated with that target class, and (b) the feature vector (X) also lies within an acceptance boundary restricting the area of that Voronoi polygon.

Patentansprüche

1. Verfahren zur Prüfung eines Geldgegenstands durch Bestimmen, ob der Gegenstand zu einer einer bestimmten Benennung in einer bestimmten Orientierung zugeordneten Zielklasse gehört, wobei das Verfahren die Erzeugung eines den Gegenstand beschreibenden k-dimensionalen Merkmalsvektors (X), die Bestimmung desjenigen Zielvektors (W_c) unter einer Vielzahl an sämtlich der genannten Zielklasse zugeordneten Zielvektoren, der am dichtesten an dem Merkmalsvektor (X) liegt, und die Bezeichnung des Gegenstands als zu der Zielklasse gehörend, wenn die Komponenten des Merkmalsvektors (X) ein vorbestimmtes Kriterium erfüllen, das angibt, daß der Merkmalsvektor (X) innerhalb einer den dichtesten Zielvektor (W_c) umfassenden vorbestimmten Grenze liegt, aufweist.

2. Verfahren nach Anspruch 1, wobei bestimmt wird, daß die Komponenten des Merkmalsvektors (X) das vorbestimmte Kriterium erfüllen, wenn der dichteste Zielvektor (W_c) eine vorbestimmte Beziehung zu dem Merkmalsvektor (X) aufweist.

3. Verfahren nach Anspruch 2, wobei die vorbestimmte Beziehung in Abhängigkeit davon, welcher Zielvektor am dichtesten liegt, unterschiedlich ist.

4. Verfahren nach einem der vorhergehenden Ansprüche, wobei bestimmt wird, daß die Komponenten des Merkmalsvektors (X) das vorbestimmte Kriterium erfüllen, wenn die einzelnen Komponenten jeweils ein entsprechendes Kriterium erfüllen.

5. Verfahren nach Anspruch 4, wobei bestimmt wird, daß die Komponenten des Merkmalsvektors (X) das vorbestimmte Kriterium erfüllen, wenn die Differenz zwischen jeder einzelnen Komponente des Zielvektors (W_c) und der entsprechenden Komponente des Merkmalsvektors (X) innerhalb eines vorbestimmten Bereichs liegt.

6. Verfahren nach einem der vorhergehenden Ansprüche, wobei jeder der einer Zielklasse zugeordneten Zielvektoren innerhalb eines entsprechenden Voronoï-Polygons liegt und das vorbestimmte Kriterium die Fläche des Voronoï-Polygons, innerhalb dessen ein Merkmalsvektor (X) als einen Gegenstand der Zielklasse darstellend angesehen wird, beschränkt.

7. Verfahren nach einem der vorhergehenden Ansprüche, wobei der am dichtesten an dem Merkmalsvektor (X) liegende Zielvektor (W_c) durch Messen des Euklidischen Abstands zwischen dem Zielvektor (W_c) und dem Merkmalsvektor (X) bestimmt wird.

8. Verfahren nach einem der vorhergehenden Ansprüche, wobei mindestens ein neuronales Netzwerk zur Bestimmung des am dichtesten an dem Merkmalsvektor (X) liegenden Zielvektors (W_c) verwendet wird.

9. Verfahren nach Anspruch 8, wobei das neuronale Netzwerk ein LVQ-Netzwerk darstellt.

10. Verfahren nach Anspruch 8 oder 9, wobei für jeden Zielvektor einer Zielklasse der Abstand d zu dem Merkmalsvektor (X) unter Verwendung eines Neuronen- oder neuronenähnlichen Elements berechnet wird.

11. Verfahren nach einem der vorhergehenden Ansprüche mit einem Schritt zur Gewinnung des Merkmalsvektors (X) unter Verwendung gespeicherter für die Zielklasse repräsentativer statistischer Daten.

12. Verfahren nach Anspruch 11, mit einem Schritt zur Aktualisierung der für die Zielklasse repräsentativen statischen Daten auf der Grundlage von Messungen an einem Prüfmuster, das als zur Zielklasse gehörig bestimmt wurde.

13. Vorrichtung zur Prüfung eines Geldgegenstands mit einem Meßsystem, einem Vorverarbeitungssystem und einem Klassifizierungssystem zur Klassifizierung eines Gegenstands, der durch einen k-dimensionalen Merkmalsvektor (X) beschrieben werden kann, wobei das Vorverarbeitungssystem auf von dem Meßsystem gelieferte Messungen physikalischer Merkmale eines Prüfmusters anspricht, um den k-dimensionalen Merkmalsvektor (X) zu gewinnen und ihn an das Klassifizierungssystem zu liefern, wobei das Klassifizierungssystem eine Erkennungseinheit zur Bestimmung, ob der Gegenstand zu einer eine bestimmte Benennung in einer bestimmten Orientierung darstellenden Zielklasse gehört, aufweist, und wobei die Erkennungseinheit im Betrieb bestimmen kann, welcher unter einer Vielzahl an der Zielklasse zugeordneten Zielvektoren der zu dem Merkmalsvektor (X) dichteste Zielvektor (W_c) ist, und den Gegenstand als zu der Ziel-

klasse gehörig benennen kann, wenn die Komponenten des Merkmalsvektors (X) ein vorbestimmtes Kriterium erfüllen, das angibt, daß der Merkmalsvektor (X) innerhalb einer den dichtesten Zielvektor (W_c) umfassenden Grenze liegt.

14. Vorrichtung nach Anspruch 13, wobei die Erkennungseinheit eine Eingabeschicht und eine an ihrer Eingangsseite über Eingangs- Gewichtungskomponenten mit der Eingangs schicht und an ihrer Ausgangsseite mit einer Ausgangsschicht verbundene neuronale Schicht aufweist, wobei die Eingangs- Gewichtungskomponenten die Zielvektoren für die Erkennungseinheit festlegen.

15. Vorrichtung nach Anspruch 14, wobei die Gewichtungskomponenten jeweils Werte aufweisen, die während eines Lernvorgangs bestimmt wurden.

16. Vorrichtung nach Anspruch 14 oder 15, mit einer Einrichtung zur Änderung der Werte der Gewichtungskomponenten entsprechend gemessener physikalischer Merkmale eines Prüfmusters, wenn das Prüfmuster als zur Zielklasse der Erkennungseinheit mit diesen Gewichtungskomponenten gehörig befunden wurde, und wenn die Gewichtungskomponenten den am dichtesten bei dem Merkmalsvektor (X) für dieses Muster liegenden Zielvektor festlegen.

17. Vorrichtung nach einem der Ansprüche 13 bis 16, wobei das Vorverarbeitungssystem verschiedene Merkmalsvektoren (X) für entsprechende Zielklassen auf der Grundlage unterschiedlicher Sätze statistischer Daten bestimmen kann, die jeweils einer entsprechenden Benennung zugeordnet sind, wobei die entsprechenden Merkmalsvektoren (X) jeweils an eine entsprechende Erkennungseinheit angelegt werden.

18. Vorrichtung nach Anspruch 17, mit einer Einrichtung zur Veränderung der eine Benennung betreffenden statistischen Daten entsprechend der gemessenen physikalischen Merkmale eines Gegenstands, der geprüft wurde, in Reaktion auf die Bestimmung, daß der Gegenstand zu der der Benennung zugeordneten Klasse gehört.

19. Verfahren zum Prüfen eines Geldgegenstands, aufweisend:

Liefern eines Signals, das angibt, daß der Geldgegenstand zu einer einer bestimmten Benennung in einer bestimmten Orientierung zugeordneten Zielklasse gehört, wenn (a) ein den Gegenstand beschreibender Merkmalsvektor (X) als innerhalb eines einer Vielzahl von der Zielklasse zugeordneten Voronoï-Polygonen liegend bestimmt wurde und (b) der Merkmalsvektor (X) außerdem innerhalb einer die Fläche des Voronoï-Polygons beschränkenden Akzeptanzgrenze liegt.

Revendications

1. Un procédé de validation d'un article d'espèces monétaires, en déterminant si l'article appartient à une classe cible associée à une dénomination particulière dans une orientation particulière, le procédé comprenant les étapes consistant à produire un vecteur caractéristique (X) à k dimensions qui décrit l'article, déterminer dans une série de vecteurs cibles qui sont tous associés à ladite classe cible le vecteur cible (W_c) qui est le plus proche du vecteur caractéristique (X), et désigner l'article comme appartenant à la classe cible si les composants du vecteur caractéristique (X) satisfont à un critère prédéterminé qui indique que le vecteur caractéristique (X) est situé à l'intérieur d'une limite prédéterminée qui contient le vecteur cible le plus proche.

2. Un procédé selon la revendication 1, dans lequel il est déterminé que les composants du vecteur caractéristique (X) satisfont audit critère prédéterminé s'il existe une relation prédéterminée entre le vecteur cible le plus proche (W_c) et le vecteur caractéristique (X).

3. Un procédé selon la revendication 2, dans lequel la relation prédéterminée diffère selon le vecteur cible le plus proche.

4. Un procédé selon une revendication précédente quelconque, dans lequel il est déterminé que les composants du vecteur caractéristique satisfont audit critère prédéterminé si les composants individuels satisfont chacun à un critère respectif.

5. Un procédé selon la revendication 4, dans lequel il est déterminé que les composants du vecteur caractéristique (X) satisfont audit critère prédéterminé si la différence entre chaque composant individuel du vecteur cible (W_c) et le composant correspondant du vecteur caractéristique (X) est à l'intérieur d'une plage prédéterminée.

6. Un procédé selon une revendication précédente quelconque, dans lequel chacun des vecteurs cibles associés à une classe cible est situé à l'intérieur d'un polygone de Voronoï, et dans lequel ledit critère prédéterminé restreint la superficie du polygone de Voronoï à l'intérieur duquel un vecteur caractéristique (X) est estimé représenter un article de la classe cible.

7. Un procédé selon une revendication précédente quelconque, dans lequel le vecteur cible (W_c) le

plus proche du vecteur caractéristique (X) est déterminé en mesurant la distance euclidienne entre le vecteur cible (W_c) et le vecteur caractéristique (X).

8. Un procédé selon une revendication précédente quelconque, dans lequel un réseau neural est utilisé pour déterminer le vecteur cible (W_c) le plus proche du vecteur caractéristique (X).

9. Un procédé selon la revendication 8, dans lequel le réseau neural est un réseau à quantification de vecteur par apprentissage.

10. Un procédé selon la revendication 8 ou la revendication 9, dans lequel, pour chaque vecteur cible d'une classe cible, la distance d au vecteur caractéristique (X) est calculée en utilisant un neurone ou un élément du type neurone.

11. Un procédé selon une revendication précédente quelconque, incluant l'étape consistant à dériver le vecteur caractéristique (X) en utilisant des données statistiques mémorisées respectives de la classe cible.

12. Un procédé selon la revendication 11, incluant l'étape consistant à mettre à jour les données statistiques respectives de la classe cible sur la base de mesures d'un spécimen de test déterminé comme appartenant à cette classe cible.

13. Appareil de validation d'espèces, l'appareil comprenant un système de mesure, un système de traitement préliminaire et un système de classement, pour le classement, ou tri, d'un article qui peut être décrit par un vecteur caractéristique (X) à k dimensions, le système de traitement préliminaire répondant à des mesures de caractéristiques physiques d'un spécimen de test fournies par le système de mesure pour dériver le vecteur caractéristique (X) à k dimensions et fournir le vecteur caractéristique à un système de classement, le système de classement comprenant une unité de reconnaissance pour déterminer si l'article appartient ou non à un classe cible qui représente une dénomination particulière dans une orientation particulière, l'unité de reconnaissance pouvant être mise en ce uvre pour déterminer, dans une série de vecteurs cibles associés à cette classe cible, le vecteur cible (W_c) qui est le plus proche du vecteur caractéristique (X), et pour désigner l'article comme appartenant à la classe cible si les composants du vecteur caractéristique (X) satisfont à un critère prédéterminé qui indique que le vecteur caractéristique (X) est situé à l'intérieur d'une limite prédéterminée contenant le vecteur cible (W_c) le plus proche.

14. Appareil selon la revendication 13, dans lequel l'unité de reconnaissance inclut une couche d'entrée, et une couche de neurones connectée à son côté d'entrée avec la couche d'entrée par des composants de pondération d'entrée et à son côté de sortie avec une couche de sortie, les composants de pondération d'entrée définissant les vecteurs cibles pour l'unité de reconnaissance.

15. Appareil selon la revendication 14, dans lequel chaque composant de pondération possède une valeur qui a été déterminée pendant un processus d'apprentissage.

16. Appareil selon la revendication 14 ou 15, incluant un moyen destiné à faire varier les valeurs des composants de pondération en fonction de caractéristiques physiques mesurées d'un spécimen de test lorsque l'on a trouvé que ce spécimen de test appartient à la classe cible de l'unité de reconnaissance incluant ces composants de pondération, et lorsque les composants de pondération définissent le vecteur cible le plus proche du vecteur caractéristique (X) pour ce spécimen.

17. Appareil selon l'une quelconque des revendications 13 à 16, dans lequel le système de traitement préliminaire peut être mis en oeuvre pour dériver des vecteurs caractéristiques (X) différents pour des classes cibles respectives sur la base d'ensembles différents de données statistiques associes chacun à une dénomination respective, les vecteurs caractéristiques (X) respectifs étant appliqués chacun à une unité respective de reconnaissance.

18. Appareil selon la revendication 17, incluant un moyen de modification des données statistiques liées à une dénomination en fonction de caractéristiques physiques mesurées d'un article qui été testé un réponse à une détermination que l'article appartient à la classe associée à cette dénomination.

19. Un procédé de validation d'un article d'espèces, le procédé comprenant l'étape consistant à fournir un signal qui indique que l'article d'espèces appartient à une classe cible associée à une dénomination particulière dans une orientation particulière si (a) un vecteur caractéristique (X) descriptif de l'article a été déterminé comme situé à l'intérieur de l'un des polygones d'une série de polygones de Voronoï associés à cette classe cible, et (b) le vecteur caractéristique (X) est lui aussi situé à l'intérieur d'une limite d'acceptation qui restreint la superficie de ce polygone de Voronoï.

FIG.1

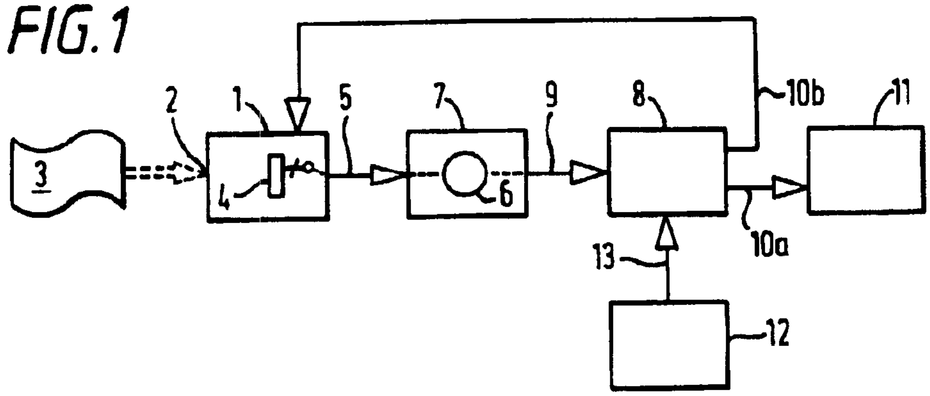


FIG.2

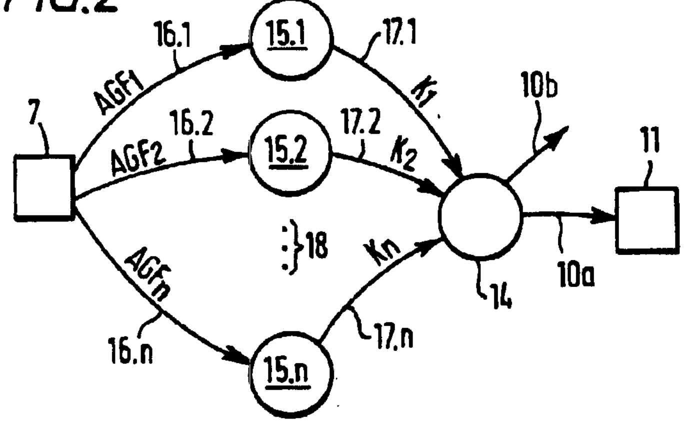
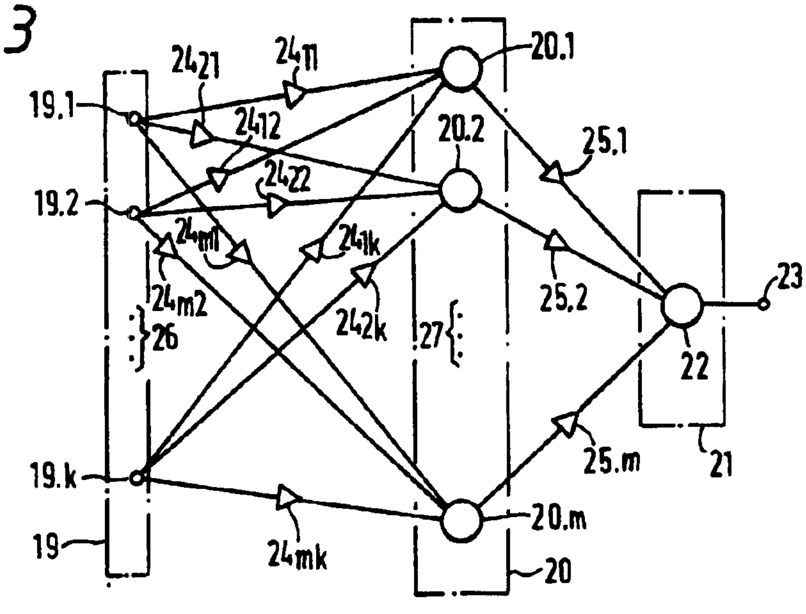
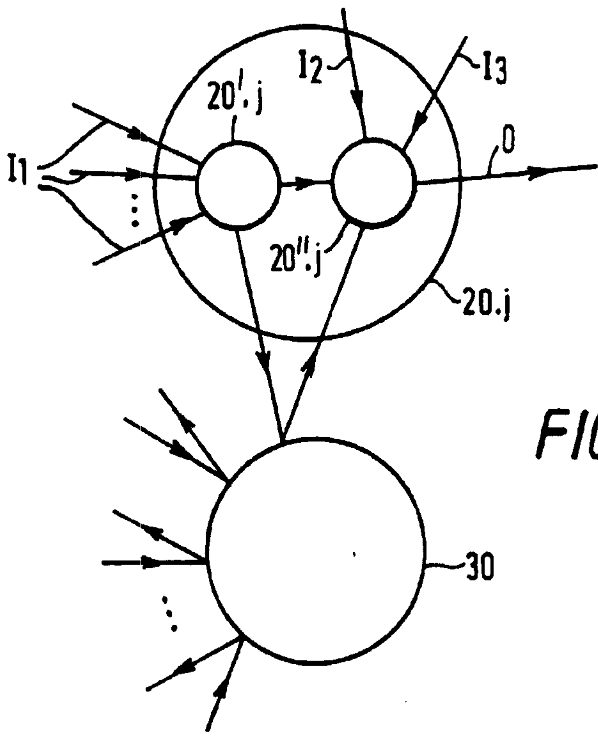


FIG.3




I1
I2
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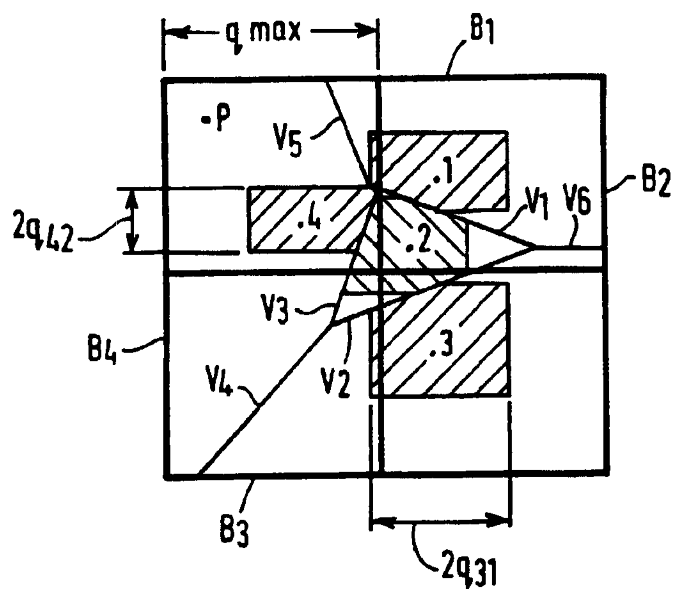
30

FIG.4

FIG.5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B3
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V5
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V3
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